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ABSTRACT

The technique of causal modeling as applied to theoretical constructs in teacher education is demonstrated. The abstract principles of causality are explained, and are applied to various educational research needs. An example is made using data collected from a sample of 44 secondary level students who participated in a one semester student teaching program at Texas A and M University. Diagrams and statistical information are included. (LH)

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# Causal Modeling and Research on Teacher Education

U S DEPARTMENT OF HEALTH, EDUCATION & WELFARE NATIONAL INSTITUTE OF EDUCATION

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One nettlesome problem affecting research in teacher education has been the lack-of articulation between conceptual positions and empirical validation of those positions. The distance between verbal descriptions, so common in teacher education, and empirically verified principles is vast. This situation is due in part to; the language used in the theories for teacher education, the operational definitions used to define the variables to be measured, and the statistical tools used in empirical verification. An additional difficulty occurs when we attempt to use an experimental design well suited for the laboratory but ill-suited for an operating classroom. Random assignment and stringent control of independent variables are often compromised in order to gain access to "real" learners. These adjustments result in quasi-experimental designs yielding results which cannot be generalized to other settings.

Further, when tests of significance are the focus of the analysis, we tend to be satisfied with significant results, and fail to relate the variables under consideration to an overall model or theory. Alternate methods allowing causal inferences from naturalistic data have not been seriously considered. Causal techniques developed in biology and subsequently applied in economics and more recently in sociology hold promise for inferential research and model verification in teacher education (Anderson & Evans; 1974). The purpose of this paper is to demonstrate how this technique, that is, causal modeling, can be applied to theoretical constructs in teacher education where data are collected in naturalistic settings.

### BACKGROUND ON GAUSAL MODELING.

Basic to the specification of a Causal Model which yields accurate estimates, a is a thorough knowledge of the process being modeled.

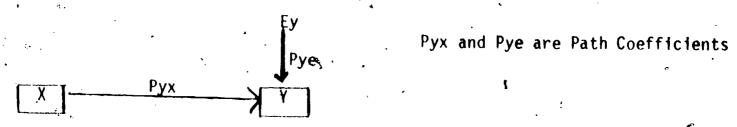
instance, all significant variables should be included in the model in a definite order. Further, the form and function of each variable in the model must be specified and there should be no interaction among the variables. Benefits from thinking causally about a problem and constructing an arrow diagram to illustrate causal processes include generating additional insights into the topic and clearer statements of hypotheses.

In discussing the tenets of causal modeling, we will consider causation in the following sense: A is the cause of B, only if B can be changed by altering A alone. This notion of causation implies prediction and manipulation. Additionally, to understand what is meant by "alone" in the statement, it is necessary to comprehend the concepts causal order and relevant control. Note that altering A alone does not exclude the possibility that all other causes of B are conrolled or held constant. If we change A alone, this adjustment may bring about changes in many other variables that are influenced by A. These changes in other variables need not be controlled when we examine the effect of A on B (Kim & Kohout', 1975).

The preceding explanation of causation assumes that in order to state that A is a cause of B, one must perform an "ideal" experiement in which other variables affecting B are held constant, while A is being altered. This, "ideal" experiment is the underlying theory or theoretical model which forms the basis for assuming the relationship between A and B. Additionally, the theoretical model is expressed as a linear, additive and unidirectional system. Given these guidelines, the relation between A and B can be expressed as a linear function:  $B=\alpha A$ , where  $\alpha$  represents the magnitude of change in B when A changes one unit. This coefficient,  $\alpha$ , is called the effect coefficient. The effect coefficient is equivalent to a coefficient ima regression equation if the assumptions of causal order and causal closure are met (Kim, Kohout, 1975). If we interpret regression coefficients as effect

performing a path analysis. <u>Causal order</u> simply means that a sequence among the variables must occur. To illustrate, X<sub>o</sub> precedes X<sub>1</sub> and may affect X<sub>1</sub> but X<sub>1</sub> <u>cannot affect</u> X<sub>o</sub>. Generally, this ordering is accomplished in terms of time of occurrence of the variable or measurement of the variable in the total system. The second assumption, <u>causal closure</u> asserts that for a causal relation between X and Y to occur, the covariation between these variables should not vanish when the effects of confounding variables (those variables causally prior to both X and Y) are removed. This limitation requires that we rule out all other possible causal factors. On what basis can we be sure we have satisfied this assumption? The answer as you might expect relates to the variables in the theoretical model or construct which provides the basis for the inquiry (Asher, 1976).

The aforementioned assumptions of order and closure are illustrated in the following two variable path diagrams:



The assumption regarding causal order, is illustrated by the direction of the arrow from X to Y. Conversely, causal closure isn't quite so apparent, yet it is addressed with the inclusion of the error term (Ey). The error component represents all residual causes of Y not accounted for by X.

AN EXAMPLE OF CAUSAL MODELING

# Theoretical Model

As the preceding discussion suggests, causal inference procedures begin with a statement of the verbal theory which makes explicit the causal

order and closure. In this paper, a five phase conceptual model of teaching (Armstrong, Denton, Savage, 1978) serves this function. This model describes teaching as a series of sequential events requiring five distinct sets of instructional skills, that is, Specifying Performance Objectives, Diagnosing Learners, Selecting Instructional Strategies, Interacting With Learners, and Evaluating the Effectiveness of Instruction.

Specifying Performance Objectives - The decisions inherent in this element of the instructional model are instrumental in determining whether the entire instructional process can be successful in producing student learning. Restated, this idea becomes performance objectives determine the direction and focus of instruction. When performance objectives are selected and sequenced according to a logical plan, teachers are in a position of leadership and can justify their program to responsible critics. Beginning with objectives in planning for teaching is a well-established procedure (Tyler, 1950; Taba, 1962; Zais, 1976) in the literature on curriculum.

Diagnosing Learners - Teachers need information regarding a learner's readiness to begin a proposed new instructional sequence. The readiness of learners in this instance pertains to whether they have attained relevant prerequisite knowledges and skills necessary to acquire the objectives established for an instructional sequence (Gagne, 1970, Glaser, 1966). Bypassing this step in an effort to save instructional time is false economy, since the result may well be frustrated, bored and unmotivated learners. When adequate diagnostic information is available, instructional plans can be developed that meet the informational and emotional needs of the learners.

Selecting Instructional Strategies - In selecting instructional strategies meachers should structure activities that are consistent with the identified performance objectives, the entry levels of the learners; and the events of

instruction espoused by Gagne & Briggs (1974). In a sense, selecting instructional strategies is analogous to generating directional research hypotheses. A strategy is created from a wide range of possible approaches which, in the teacher's mind, will likely bring about learner attainment of the performance objectives. The appropriateness of this strategy is "tested" during the implementation and evaluation phases of instruction. Justification for the position of this component in the model again is drawn from literature on curriculum development (Taba, 1962; Tyler, 1950) and instructional design (Davies, 1973; Glaser, 1966).

Interacting with Learners - This component represents the "doing as implementation phase" of the instructional model. The elegance of the instructional plan becomes unimportant if the timing and continuity of the classroom activities are interrupted creating disorder and predictable management problems. Thus, learning how to interact with learners is, perhaps, the most difficult set of skills for new teachers to attain.

Mastering these skills requires considerable practice in actual classroom settings, and serves to justify the emphasis on the student teaching experience in teacher preparation programs. Pragmatically, this phase occurs after the instructional unit has been planned and developed. Thus, its position in the model is established by logical and practical considerations.

Evaluating the Effectiveness of Instruction - This component serves to gather evidence during and after the teaching of an instructional unit to determine whether the plan "worked." Evaluation should prompt a review of each component in the instructional model. Representative questions to illustrate this review include: Were the performance objectives appropriate? Were the pretests really diagnostic tools? Did the instructional strategies incorporate the events of instruction? Was classroom management sufficient

valid for assessing learner growth and program effectiveness? These questions are characteristic of summative evaluation concerns (Scriven, 1967) and product evaluation (Stufflebeam, Foley, Gephart, Guba, Hammond, Merriman, Provus, 1971). Thus justification for the position of this final component in the teaching model is drawn from the professional literature on evaluation.

This model provides a framework that encourages the development of individual teaching styles. Individualized styles are encouraged because evaluation of instruction is based on learner attainment of performance objectives. Given this operating principle, teachers in preparation are free to choose procedures from their own repertoires that they believe will result in high levels of learner performance. Further, teacher responsibility is well served by this model. This responsibility comes not because of the teaching candidate's adherence to a set of "ideal role behaviors," but rather in adapting instructional practice, as necessary, to help learners achieve performance objectives that have been selected.

# Causal Model

Translating this conceptual verbal model into hypothetical causal relations is the function of the diagram provided in figure 1. As indicated previously, the path diagram indicates linear, additive relations among the five variables that are included in the model.



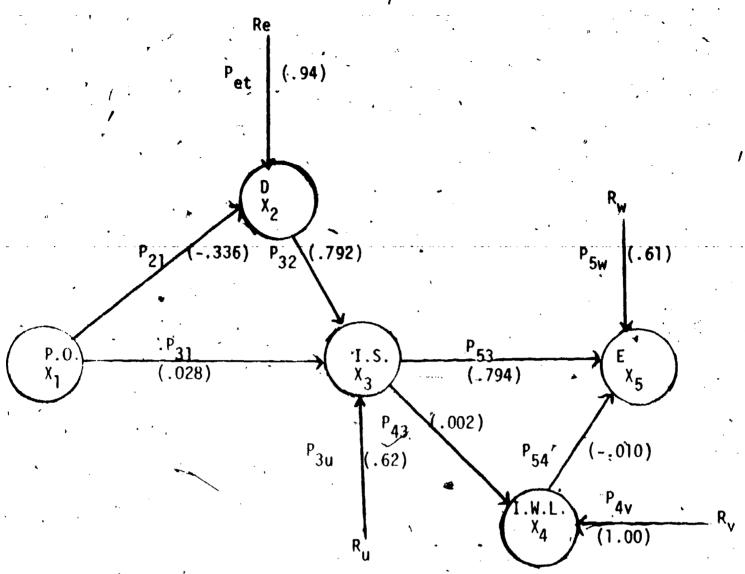


Figure 1

Recursive Path Model for a Model of Teaching

P.O.= $(X_1)$  = Performance Objectives Component,  $D=(X_2)$  = Diagnosis Component E.S.= $(X_3)$  = Instructional Strategies Component,  $IWL=(X_4)$  = Interacting with Learne Component,  $E=(X_5)$  = Evaluation Component,  $P_{ij}$  = Path Coefficients

Only the initial variable in the model is exogenous, that is,  $X_1$  is not influnced by the other variables in the model. The remaining four variables,  $X_2$ ,  $X_3$ ,  $X_4$ ,  $X_5$ , are considered to be endogenous and as such are determined completely by variables within the model as well as the residual variables, i.e.,  $R_t$ ,  $R_u$ ,  $R_v$ ,  $R_w$ . These residual variables represent the effects of all other variables not included in the model but which cause variation in the endogenous variables. Stated another way, the exogenous and endogenous variables  $(X_{i \mid s})$  are unmeasured variables for which values have not been obtained. The  $P_{ij \mid s}$  at this point

refer to unknown values representing the effect of one variable  $(X_j)$  on another  $(X_j)$  (Asher, 1976).

Once the path model has been developed, a set of structural equations can be written. One fully defined structural equation can be listed for each endogenous variable in the model. In the case of our path model for teaching four structural equations can be developed. These are:

$$X_2 = P_{21}X_1 + P_{2t}R_t$$
  
 $X_3 = P_{31}X_1 + P_{32}X_2 + P_{3u}R_u$   
 $X_4 = P_{43}X_3 + P_{4v}Rv$   
 $X_5 = P_{53}X_3 + P_{54}X_4 + P_{5w}R_w$ 

Simple muliple regression can be used to estimate the various path coefficients in path models such as the model presented in figure 1 where there are no feedback loops ( $\longrightarrow$ ) between any of the variables. The path coefficients,  $P_{ij}$ , which are associated with various arrows in figure 1 are standardized Beta coefficients: that is,  $P_{21} = B_{21}$ . These path coefficients are thought to measure the proportion of the standard deviation of the dependent (endogenous) variable directly accounted for by an independent (exogenous) variable when the influence of all other variables are removed (Land, 1969). Standardized Beta coefficients from the four linear equations representing the various path coefficients in figure 1 are presented in the following table.

Table 1

Standardized Regression Coefficients (Path Coefficients) for the Four
Structural Equations Related to the Model of Teaching

Dependent Variable	Independent Variable	Path label (P <sub>ij</sub> )	Standardized Regression Coefficient (B)	Coeffici <b>ent</b> of Determinate (R <sup>2</sup> )
Diagnosis (X <sub>2</sub> )	Performance Objective	P <sub>21</sub>	336	.113
Instructional (X <sub>3</sub> ) Strategies . 3	Performance Objectives	P <sub>31</sub>	:028	.614
	Diagnosis	P <sub>32</sub>	.792	
Interacting (X <sub>4</sub> ) with Learners	Instructional Strategies	P <sub>43</sub>	.002	.000
Evaluation $(X_5)$	Instructional Strategies	P <sub>53</sub>	794	. 631
• .	Interacting with Learners	P <sub>54</sub>	010	

These estimates are based on data collected from a sample of 44 secondary level student teachers who participated in a full semester-full day student teaching program offered by the department of educational curriculum & instruction at Texas A&M University. During this experience, each student teacher is required to develop and implement two instructional units in a manner consistent with the model of teaching being validated in this analysis. Evaluation of student teachers in this program includes supervisor ratings based on in-class observations and supervisor assessments of instructional materials produced by the student teacher. Details concerning the nature of the sample, as well as the scales and indices that were used are described in Denton (1979) and Henson and Tooke (1980).

Given the values from the analysis of the structural equations, we can also determine the residual path coefficients in figure 1, i.e.,  $P_{2t} = .94$ ,  $P_{3u} = .62$ ,  $P_{4u} = 1.00$ ,  $P_{5w} = .61$ . These values are determined by applying the following formula.  $P_{1a} = \sqrt{1-R^2}$  where  $R^2$  is the multiple correlation



coefficient for each structural equation. As mentioned earlier, the residual path coefficient measures the effect of all unmeasured variables not included in the model that cause variation in the dependent variable. Examining the coefficients of determination ( $\mathbb{R}^2$ ) in table 1, reveals two of the structural equations are composed of variables that explain over 60% of the variance in the dependent variable under consideration. Conversely, one equation emanating from this model resulted in an  $\mathbb{R}^2$  of zero suggesting a rather serious limitation in the model specification and/or data collection procedures for the variables in the equation.

determination of the direct and indirect effects that one variable has upon another. Path analysis enables the decomposition of the correlation between any two variables into a sum of simple and compound paths. While where are a number of decomposition approaches, we have applied a technique developed by Sewall Wright (cited in Asher, 1976). Wright's approach consists of two definitions and three instructions as to how a correlation is decomposed.

The definitions are: 1. Any correlation between two variables can be decomposed into a sum of simple (direct) and compound (indirect) paths.

2. A compound path is equal to the product of the simple paths comprising it.

The corresponding instructions attributed to Wright are:

- (a) no path may pass through the same variable more than once;
- (b) no path may go backward (against the direction of) an arrow after the path has gone forward on a different arrow;
- (c) no path may pass through a double-headed curved arrow (representing an unanalyzed correlation between exogenous variables) more than once in any single path. (Asher, 976, p33).

Applying these definitions and instructions to the path coefficients listed in figure 1, decomposition of the correlations between the variables in the model have been accomplished and are reported in table 2.

Table 2

Correlation Decomposition Table for Correlations Among the Five

Variables Included in the Model of Teaching.

Variables	Zero-order	Causal		Spurious	
•	Correlation(r <sub>ij</sub> .) (A)	Direct (B)	Indirect (C)	Total (D)	(A-D) ~ ·
PO - D	336	336 +	none	336	.000
PO - IS	238 · · · · ·	. 028	266	238	000
D- IS	.783 ^	792	′. none	792	009
IS, - IWL	.002	002	none	.002	.000
İS - E	.795	.794	$2.10^{-5}$	.794	<b>3</b> 001
IWL-E	010	<sup>3</sup> 010	none	010	.000
*PO - IW1	-`.128	***0	-5.10 <sup>-4</sup>		•,
*P0-E	138	**0	189	•	•
*D IW1	. 033	**0	· .002	/	
*D - E	.729	**,0	<u>.:</u> 630		
		,			•

<sup>\*</sup> Direct causal effects between these variables were not calculated, since they were not included in the path model.

The decomposition of the correlation provides a way to test the adequancy of the model if some linkages have initially been omitted. If the model is specified correctly, the zero order correlation between any two variables should be numerically equal to the sum of the simple and compound paths linking the two variables. If the values are not equal, then the model may not be specified appropriately and be in need of revision. Further, if the zero-order correlations between variables in the model are zero or nearly so, then adjustments may be necessary. Similarly, if correlations between variables which are not connected by paths in the model greatly exceed

<sup>\*\*</sup> The causal effect of these variables pairs is assumed to be 0 since they were not included in the path model.

zero, specification concerns may be signalled.

Examining the values in table 2 reveals possible limitations in the present model given the aforementioned guidelines. For instance, path coefficients,  $P_{43} = .002$ ,  $P_{54} = .01$ , suggest errors regarding the causal links between Instructional Strategies and Interacting with Learners, and between Interacting with Learners and Evaluation, respectively. It cannot be determined from the information we have whether the difficulties lie with model specifications, variable measurement or a combination of these conceptual constructs. Yet we do know where to direct our attention in re-examining the model. Another relation which may merit additional study is signalled by the substantial correlation ( $r_{DE} = .729$ ) between Diagnosis and Evaluation. On this case no direct causal link is provided in the path model, to account for a portion of this relation. Thus, consideration of a direct path, between Diagnosis and Evaluation is reasonable advice given the model testing permitted by these path analysis techniques.

As the preceding statements reveal, path analysis procedures provide us with the means to check the conceptual association in our model of teaching. While the linkages with the component Interacting with Learners, appears to be in need of review, other aspects of the model appear to be reasonably sound.

#### SUMMARY

This paper has addressed one type of causal model involving one-way causation. The structural equations in this paper are recursive and focus on the five components of a model of teaching. Other forms of causal modeling are possible which involve reciprocal causation under certain conditions, but these non-recursive techniques have not been addressed.

Causal modeling procedures provide powerful methodological tools for

educational researchers in relating theory and research in natural stic settings. These techniques encourage a set of causal relations to be hypothesized on the basis of a theoretical framework. Subsequent to this conceptualizing effort linear regression equations based on the set of hypothetical relations are developed and treated statistically. Values obtained from this treatment provide numerical estimates of the hypothesized relations. Thus, conceptual theories in education can be transformed into their quantatative equivalents and be empirically validated by employing these procedures. Perhaps through the use of these methods, the gulf between verbal and quantitative constructs in teacher education can be reduced, resulting in better theories for teaching and preparing teachers.

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